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St. Petersburg State University
Graduate School of Management

WORKING PAPER

S. Sharapudinov, V. Zezerova, M. Storchevoy

DETERMINANTS OF ONLINE WORD-OF-MOUTH: EVIDENCE FROM DURABLE GOODS MARKET

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St. Petersburg State University
Graduate School of Management

St. Petersburg, 199004, Russia,
Volkhovskiy Pereulok, 3
tel. (812) 323 84 64, fax (812) 329 32 34

www.gsom.spbu.ru

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Abstract: Online reviews became one of the most effective tools that influence consumer behavior and level of sales. In this paper we consider determinants of online review rating. The study is based on more than three thousand online reviews from Russian consumers of durable goods (electronics and home appliances). It was found that there is a significant difference in the level of influence between new and old reviews. Moreover, the higher the total numbers of reviews available, the higher the number of reviews taken into account by a particular consumer. Another finding is that both average online rank and price of a product are positively correlated with variance of reviews on that product. Based on the differences in the effectiveness of information transmission about quality of products, products were divided into two categories: “experience” products and “search” products. At the last stage, we provide an econometric model that allows to explain not only dynamic but also the direction of consumers’ rank of a product.

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S. Sharapudinov — Research Fellow, National Research University Higher School of Economics
e-mail: ssharapudinov@hse.ru

V. Zezerova — Doctoral student, National Research University Higher School of Economics
e-mail: vvzezerova@gmail.com

M. Storchevoy — Senior Lecturer, Graduate School of Management, St. Petersburg State University
e-mail: storchevoy@gsom.pu.ru

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Determinants of Online Word-of-Mouth: Evidence from Durable Goods Market

1. Introduction

Word-of-mouth marketing is one of the most effective sources of information about products and services, and has credibility among consumers [Reynolds, Beatty, 1999; Maxham, Netemeyer, 2002; Godes, Mayzlin, 2004; Nielsen Company, 2007]. Development of information technology significantly enhanced the possibilities of this communication channel which transformed into eWOM — electronic word-of-mouth which may be less personal but much more powerful. Now people with similar interests, needs and preferences can share their views, exchange information regardless of their location. This feature of online communication is widely used in modern marketing: producers and sellers create online reviews systems in order to attract new customers. Nowadays the most popular online reviews systems are generated by users who have already tried the product or service and want to share their experience.

The opportunity to learn experience of other users in a convenient and interactive way without leaving your home made online reviews one of the most powerful marketing tools. According to a study conducted by Deloitte Company [2007], 82% of respondents say that online reviews are the main factor determining their purchase decision, 23% of all online activity is devoted to online forums, and 44% of online time is spent on web-sites with ability to compare prices and ratings. According to Nielsen Company [2007], 75% of users believe that online reviews are the most valuable and reliable source of information. Positive relationship between online product ratings and its sales volume emphasizes marketing value of reviews system [Godes, Mayzlin, 2004; Chevalier, Mayzlin, 2006]. Many publications reveal positive relationship between average product rating and sales level which supports practical importance of studying dynamics of online reviews. Reviews raise awareness about the product and form an image of the product, that is why companies should monitor the "average grade" of their products. While positive reviews can improve brand positioning and increase sales, negative reviews can weaken brand's reputation and damage sales [Pfeffer, Zorbach, Carley, 2014].

Nevertheless, despite the growing interest in online ratings, it is still an open question what factors affect the decision to write a review and what factors affect the assessment besides immediate satisfaction with the product. Even though the number of reviews positively influences the awareness of future customers about the product, their estimates do not always converge which raises the question about usefulness of online reviews for certain categories of products. When online reviews do not work well, the company needs to think about additional ways to inform users about its products.

The main purpose of this study is to identify factors that influence the dynamics of online reviews, the reasons for writing a review and the indicators that influence the probability of setting a certain rating.

The paper has the following structure. The first section provides literature review for word-of-mouth marketing and online reviews to identify possible gaps in research. The second section contains descriptive statistics of online reviews data from an electronic durable goods website for 11 product categories and suggests hypotheses. The third section presents an empirical model that explains dynamics of online reviews.

2. Literature Review

Recommendations of friends and acquaintances and other forms of word of mouth were always a popular channel of spreading opinions about products significantly influencing consumer choice. In the Internet age, this channel became much more influential due to speed of information transfer as well as access to opinions of thousands people about a product. Consumers willingly share their experience through various online platforms (online stores or aggregators such as Yandex.Market) or social networks. The variety of online channels of information exchange, wide audience coverage and inessential time costs have made "word of mouth" marketing one of the most powerful tools of promoting products and services.

The most important role in this system is played by online reviews on the websites of shops and trade platforms which allow to accumulate, systematize and generalize the opinions of customers about purchased products and quality of service.

Literature devoted to online reviews can be divided into two main streams: 1) the impact of online reviews on future sales and 2) consumer motivation in writing a review.

2.1. Impact of Online Reviews on Future Sales

Research shows that there is a significant positive correlation between the average product rating in the online reviews system (valency) and the level of future sales in e-book market [Chevalier, Mayzlin, 2006; Duan, Whinston, 2008], in film industry [Eliashberg, Shugan, 1997; Basuroy, Chatterjee, Ravid, 2003], in video game market [Zhu, Zhang, 2010], in beer market [Clemons, Gao, Hitt, 2006]. However, some scientists still dispute the fact of such dependence [Duan, Gu, Whinston, 2005]. Some authors [De Langhe, Fernbach, Lichtenstein 2015; Kozinets, 2016] argued that consumers trust average user ratings as indicators of objective product performance much more than they should.

There is disagreement about comparative influence of positive and negative reviews. One of the most famous works in this topic is a comparative study of two online stores Amazon.com and Barnesandnoble.com [Chevalier, Mayzlin, 2006]. Based on the regression analysis of reviews for more than 3,000 books, the authors concluded that negative reviews have more significant impact on sales than positive ones. In addition, the authors found that users tend to give higher ratings than their real assessment. These findings were confirmed by a number of other studies which demonstrated that complaints and sharply negative reviews may reduce sales [Luo, 2007]. Negative reviews lead to a reduction in prices for products of the highest price category, while positive reviews only increase price of cheap product [Chatterjee, 2001]. Increase in the number of comments and product ratings increases sales [Duan, Gu, Whinston, 2005; Liu, 2006; Forman, Ghose, Wiesenfeld, 2008].

In addition to valence and volume of online reviews, the third important factor affecting sales is the dispersion of online reviews. Research of film market [Sun, 2012] and beer market [Clemons, Gao, Hitt, 2006] showed that ratings dispersion has significant negative impact on sales, which means that the seller should try not only to increase average rating, but also to control dispersion of ratings.

2.2. Consumer Motivation in Writing a Review

The second direction investigates motivation for writing online reviews. Early works on traditional word of mouth distinguished the following factors explaining the decision to write a review by consumers: deep interest in the product (brand loyalty, trend), need for self-involvement (opportunity to gratify emotional needs connected with usage of product), necessity for discussion, altruism (act of helping without anticipating any reward, desire of users to share bad experience to prevent people from usage of bad quality products or on the contrary to advise people products with good quality to prevent any wrong choice), desire to get help (advice seeking), self-enhancement (opportunity to gain attention, suggest status, recommend yourself as an expert in this filed) [Dichter, 1966; Sundaram, Mitra, Webster, 1998].

A similar study for online reviews was first conducted by a group of German scholars [Hennig-Thurau et al., 2004]. Based on the survey of more than 2,000 active users of systems with online reviews support and forums, the authors identified seven main motivations for participating in word-of-mouth, six of which completely coincide with the results of previous studies. Beside this, several other motives were highlighted: the desire to influence the quality of the product, because companies need to pay attention to negative experiences of its users.

According to [Ho, Wu, Tan, 2014] the desire to write an online review depends not only on the motives that arise after the purchase, but also on user's behavior before buying. The desire to write a review depends on the difference between the expected quality of the product and what the buyer actually received (quality mismatch). When this difference is sufficiently high, the user decides to share his experience. His rating in turn depends on the difference between the observed average rating on the web-site and the user's own estimation of product. This paper not only provides a theoretical basis for the hypotheses, but also builds an empirical model based on the method of ordinary least squares (OLS) and Monte Carlo method. Similar conclusions were obtained in other works [Spreng, MacKenzie, Olshavsky, 1996; Anderson, Sullivan, 1993; Hu, Liu, Zhang, 2008].

Some authors [Fu, Ju, Hsu, 2015] emphasize that intentions to engage in positive and negative online reviews are associated with different antecedents. Consumers who intend to post positive reviews are more driven by attitude, and consumers who consider posting negative reviews are more driven moral norms. Other authors [Balaji, Khong, Chong, 2016] focus mostly on decisions to write a negative review. On the basis of the self-reported retrospective survey of 206 online shoppers the authors reveal the role of contextual, individual and social networking factors in determining the customers' intentions to engage in negative word-of-mouth communication.

Another motive for participation is the self-enhancement motive: users often write reviews which are knowingly controversial related to the average rating or the last reviews trying to distinguish themselves from the general content of reviews [Hu, Liu, Zhang, 2008; Li, Hitt, 2008].

There is also a number of works that study factors influencing specific rating. In the paper [Gao, Gu, Lin 2006] based on the analysis of online reviews at CNET.com, it was found that a user's rating depends positively on the average rating of all reviews, the last review for this product, and expert's review, while the influence of the expert's evaluation is more significant than the other two factors. An interesting result was received by researchers [Hu, Liu, Zhang, 2008], who found that the influence of positive and negative reviews depends on the personal characteristics of the user. The biggest impact is made by reviews of users with a good expert reputation, as well as those who often write reviews in this system. The paper [Aerts, Smits, Verlegh, 2017] investigates how the design of the online review platform may influence the content of the reviews.

However, recent works devoted to experts' reviews [Baber et al., 2016] argues that the average rating across all users tends to be more significant than reviews of experts.

In addition, it is worth noting not only the influence of quantitative assessments, but also the content of the reviews. In the paper [Hennig-Thurau, Wiertz, Feldhaus, 2015] it was shown that if there is only comment evaluation without quantitative ratings, users read more carefully negative comments, therefore the influence of negative comments on purchasing decisions is higher. Salehan and Kim [2016] investigated the predictors of readership and helpfulness of online consumer reviews using a sentiment mining approach for big data analytics. They found that with higher levels of positive sentiment in the title receive more readerships. Sentimental reviews with neutral polarity in the text are also perceived to be more helpful. The length and longevity of a review positively influence both its readership and helpfulness. The author suggested that online vendors should develop scalable automated systems for sorting and classification of big online reviews data which will benefit both vendors and consumers. Singh and others [2017] also focused on the problem of handling the large number of online reviews and developed a model based on machine learning that can predict the helpfulness of the consumer reviews using several textual features such as polarity, subjectivity, entropy, and reading ease. The model may automatically assign helpfulness values to an initial review as soon as it is posted on the website.

2.3. Quality and Types of Products

An interesting direction of research is focused on the influence of online reviews for different types of products. In the economics of information, there is a distinction between search products and experience products [Nelson, 1970; 1974]. Consumer can easily get information about quality and utility of search products before purchase (e.g. gasoline or paper). However, consumer can reveal the quality and subjective utility of experience products only after buying and consuming them (e.g. a new phone model or a new author's book) [Hong, Chen, Hitt, 2014].

With development of Internet the cost of receiving information radically changed. It made some authors suppose that Internet turns some experience products into search products [Klein, 1998; Lynch, Ariely, 2000; Klein, Ford, 2003]. Since consumer can read online reviews of new books or phones, and also test some products online (e.g. software, games), the division into search products and experience may be put into the question. However, this hypothesis caused a series of empirical studies based on the results of a survey of Internet users indicating that there still exists a significant difference between product types [Thakor, Kumar, 2000; Krishnan, Hartline, 2001; Weathers, Makienko, 2006; Nakayama, Sutcliffe, Wan, 2010].

Online reviews as an instrument for evaluation of type of product were first used in [Hong, Chen, Hitt, 2014]. The authors argue that it is difficult to attribute products to one or another type of products, so it is more logical to consider each product as a combination of attributes (characteristics) of search and experience. The search attributes reflect the objective quality of the products, so information about them helps the buyer to get an idea of the product. Attributes of experience describe the subjective component of quality, therefore information about these characteristics is less useful for the buyer. Depending on which attributes prevail in the product, online reviews will have different effect on reduction of uncertainty about the quality of the product. For traditional search products, an increase in the number of reviews leads to a convergence of estimates of online reviews, while for products of experience the dispersion of reviews increases. The number of online reviews positively correlates with the dispersion of reviews for products with dominant attributes of experience and negatively correlates with the spread of product ratings with dominant search attributes. Authors consider cumulative standard deviation as a measure of information diffusion effectiveness and a tool to distinguish search and experience products. In case of search products information transfer through online reviews should be effective and that is why we should see convergence of online reviews. By convergence is understood decrease in cumulative standard deviation with increase in number of reviews. In case of experience products information exchange doesn’t provide very clear idea about quality of product, that is why growth of online reviews shouldn’t cause decrease variance of ratings and with growth of number of reviews cumulative standard deviation shouldn’t decrease.

Although experience products bring a greater uncertainty about the quality of the products, expressed in a large variance of estimates, if the user associates such a variation with the difference in preferences, and not with the quality of the products, this can serve as an additional incentive to buy product for risk lovers [He , Bond, 2015].

Despite the considerable interest in the topic there are still open questions to think about. First, research is limited to few segments: film and book markets. Secondly, it can be noted that almost all papers are focused on the influence of online reviews on sales, while consumer behavior in writing reviews is rarely studied. Thirdly, extant research is limited to three main parameters of online reviews — average overall rating, number of reviews and variance of reviews, while impact of individual review characteristics is not considered. There is also a gap in understanding how previous reviews may influence the following variables: difference between new and old ratings, importance of user experience, motives, impact of positive and negative reviews, textual information, support of online community, influence of the type of product on decision to write a review. These factors seem to be significant to explain the dynamics of online reviews, so our study will focus on them.

Apart of variables that were not considered in previous papers, this research will also investigate motives for writing reviews and product types as factors influencing dynamic of online reviews. Product type and effectiveness of information transfer can also be one of factors describing dynamic of ratings formation.

This paper investigates online reviews of Russian consumers in the electronic durable goods market. Since most of extant research focus on US and Chinese market, analysis of Russian data is interesting from both scientific and practical perspectives. First, this paper will help to understand if there is empirical evidence for motives that were postulated based on users behavior in USA and China. Second, as it was stated in literature review, many research papers postulate influence of average grade and dispersion on product sales, that is why understanding of factors influencing its dynamic can have crucial role for producers and resellers in positioning of their product. Electronic durable goods are characterized by high online reviews activity and it was not examined in previous research.

3. Data

There are several large aggregators in Russian online retail industry that provide information about characteristics of products, allow to compare prices and accumulate online reviews. Yandex.Market[1] is the most popular service for search and comparison of products in online retail stores. It has a very rich database of online reviews as well as detailed description of products' characteristics. The web-site is well structured and has a clear classification of product categories. The user can find not only the average score for a product, but also the distribution of evaluations. In addition to the quantitative evaluation, every review can also contain a user's verbal comment, which is divided into three fields: "Merits", "Shortcomings" and "Additional information". This feedback structuring greatly simplifies the process of analyzing text variables, expanding the possibilities of analysis of product's quality satisfaction. Yandex.Market also provides detailed information about the author of the review: it is possible to see user's name and date of review, geographical location of the user, user's activity on the platform expressed in the number of written reviews. No other aggregator provides such a range of information. Another important feature of this platform is the ability to track their social acceptance — for each review there are "likes" and "dislikes". All these advantages indicate that this website is a good source for collecting data for empirical analysis.

We collected information about more than 3,500 online reviews about consumer electronic products[2]. This information was coded into 22 variables described in the following table:

Table 1. Variables of Research

Name of variable	Type	Description
id	quantitative	id number
product	textual	product name
category	categorial	product category
number_reviews	quantitative	number of product reviews for product

[1] URL: https://market.yandex.ru/

[2] The authors are grateful to E.Pokryshevskaya for help in data collection.

sequence	ordinal	order of review n product's reviews line
average_grade	quantitative	average rating before writing current review (without rounding)
avg_grade_round	quantitative	average rating before writing current review (rounded to 0,5 increments)
total_grade	quantitative	total average rating (rounded)
grade_word	textual	rating in comment (textual n comment)
grade	quantitative	rating/grade by user
author	textual	name of author
author_n_reviews	quantitative	number of reviews written by current author
experience1	dummy	product use experience (less than month)
experience2	dummy	product use experience (several months)
experience3	dummy	product use experience (more than year)
ln_advan	quantitative	logarithm of symbols number in merit comment section
ln_disadvan	quantitative	logarithm of symbols number in shortcomings comment section
ln_comment	quantitative	logarithm of symbols number in general comment section
likes	quantitative	number of likes for current review, which represent number users who found current review informative or agreed with it
dislikes	quantitative	number of dislikes for current review, which represent number users who didn't find current review informative or didn't agreed with it
days	quantitative	number of days between current and previous review
average_price	quantitative	average price of product
min_price	quantitative	minimum price of product
attributes	quantitative	number of product attributes

An important step in making data talk is its descriptive statistics. Since some data was collected automatically, there is a possibility of registration errors. In addition, this analysis helps to formulate research hypotheses by identifying certain trends and deviations in the data.

First, let us consider main aggregated metrics for online reviews for each product: average score and number of reviews among products.

Table 2. Descriptive Statistics

Variable	**Average**	**Median**	**ST.D**	**Min**	**Max**
total_grade	4,07454	4,00	0,50034	2	5
grade	4,06145	5,00	1,31800	1	5
total_reviews	276,746	191	244,481	30	854

As it is seen from the Table 2, all products have an average score of 4, with a difference of only 0,5 points between products. It is also worth noting that most of the values fall on positive ratings. This means that the products included in this study have good quality.

Data cover information about 60 products that are top discussed within electronic durable goods on Yandex.Market. They are divided into different categories based on product partition on website (refrigerators, wash machines, TVs etc.). The total list of categories is described in Table 3.

If we consider all available reviews, the deviation from the average grade increases almost threefold at the level of individual categories. Despite a slight deviation in the average grade, the distribution of ratings within each product and between products is quite heterogeneous. In addition, if we consider the grade for products within each category, it can be noted that some categories are characterized by a stronger standard deviation in the rating values (about 1,8 points), other categories are characterized by a weaker deviation (0,6).

Table 3. Descriptive Statistics by Categories

Category	Mean	ST.D	Min	Max	Skewness	Kurtosis
GPS_navigator	3,226563	1,670564	1	5	-0,26008	1,400551
TV_set	4,087838	1,222961	1	5	-1,24282	3,428682
air_conditioner	3,824074	1,490335	1	5	-0,9728721	2,415817
blender	3,800643	1,52362	1	5	-0,8177085	2,062254
camera	4,609012	0,7835872	1	5	-2,552539	10,18243
electr_book	4,093333	1,328222	1	5	-1,325753	3,405811
flatiron	4,09607	1,242321	1	5	-1,200412	3,254405
haircutting	4,478261	1,17279	1	5	-2,222873	6,492485
hairdrier	3,902857	1,329049	1	5	-0,9115099	2,496006
kettle	3,862069	1,396372	1	5	-0,915068	2,440798
laptop	4,27027	1,09098	1	5	-1,591336	4,804533
memory_card	3,034014	1,765014	1	5	-0,0292696	1,235737
playstation	4,503006	0,9555855	1	5	-2,268366	7,769983
printer	3,860606	1,422344	1	5	-0,9338909	2,435902
refrigerator	4,15625	1,196226	1	5	-1,296717	3,634723
screen	4,337209	1,088058	1	5	-1,709219	5,036268
smartphone	4,075791	1,253139	1	5	-1,271245	3,480383
vacuum_cleaner	3,666667	1,512181	1	5	-0,7190929	1,981687
video_camera	4,81982	0,5752185	1	5	-4,302837	24,48099
wash_mashine	3,67033	1,426311	1	5	-0,7127539	2,112099

As far as distribution of ratings between product categories and within the product category is heterogeneous but average category scores are practically the same, we can raise the question about factors which influence the deviation of the rating of an individual user, and whether reviews for a product converge in ratings.

In this paper we analyze the convergence of ratings through the concept of search and experience product. When online reviews converge, it may be said that this is a product of search, and in the opposite situation — a product of experience.

You can see also the number of written reviews in Table 2. On average, about 277 reviews are written for each product, but the median is significantly different from the average what indicates that most of the products have more than the average number of reviews. Products are characterized as well by high deviation in number of reviews: there is a maximum of 854 reviews for one product.

Despite the fact that each product has a long history of ratings, it is logical to assume that users do not look through all the answers, but read only the most recent ones and base their purchasing decisions on them. In addition, the number of reviews taken into consideration may also depend on the length of the reviews' history.

Hypothesis 1: New ratings have a bigger impact on the user's current review than the older ones: the higher is the variance of previous reviews, the higher the deviation of the current rating from the average accumulated score.

Table 4. Descriptive Statistics

Variable	Average	Median	SD.D	Min	Max
average_price	11125,99	7517,00	10371,91	532	85515
min_price	9250,068	7490,00	6950,85	218	48400
attributes	31,80308	23,00	21,19845	3	108

In order to reflect the influence of price factors on the variance of reviews, information was collected not only on the average, but also on the minimum price, since for many users it can be a better predictor. Table 4 shows that the products included in the study cover a broad price range: standard deviation is around 10370 rubles, with the price of some products reaching 85,515 rubles.

Despite noticeable differences between average and minimum prices, standard deviation and maximum price, it should be noted that the median value for the two prices is almost the same, indicating that the biggest difference in two prices belongs to the higher price segment. In addition, we can assume that users who buy more expensive products pay more attention to learning from the experience of other users, so the strength of the price effect will differ for products of the highest and lowest price category.

Hypothesis 2: Average and minimum prices have different power of influence on the dynamics of online reviews.

Table 4 also shows the number of attributes each product has: we see that standard deviation is rather high and range of values very high. As discussed in the first chapter of [Hong, Chen, Hitt, 2014], number of attributes can influence complexity of information communication and be closely related with types of products.

Hypothesis 3: Products differ in complexity of information communication efficiency about the quality of the product: one can distinguish search products and products of experience.

Further, a descriptive analysis of individual characteristics of the reviews was investigated.

Table 5. Descriptive Statistics of Individual Review

Variable	Average	Median	St.D	Min	Max
authors_n_reviews	7,910285	3,00	11,99602	2	179
advantages	185,1093	101,00	257,4444	0	2021
disadvantages	190,6758	99,00	267,187	0	2006
comment	380,6239	261,00	398,1937	0	2230
likes	27,38632	12,00	58,23022	0	2214
dislikes	13,93136	5,00	53,71384	0	2508

Variables presented in Table 5 are of great interest, since they reflect the content of the review. On average, an author writes 8 reviews, but the median value is much lower, what indicates that, possibly, the average for this variable is highly overestimated due to abnormally high values. The maximum value in 179 reviews per one author seemed very doubtful. Although it was not a mistake of data registration, we decided to make a test for outliers to avoid bias.

Despite the fact that the majority of ratings are positive, we see that the average length of comments describing advantages and disadvantages of products is practically the same. The average length of a comment is about 280 characters and significantly exceeds the sections of advantages and disadvantages. In this section users usually share their general perception of usage, that is why it reflects the most subjective part of the product quality assessment. These variables indicate the degree of informative feedback, as well as the ratio of negative and positive impressions about the use of the product.

The last block of variables is represented by "likes" and "dislikes" of a review. On average, each individual review has 12 "likes" and 5 "dislikes", but for some reviews, these variables exceed 2,000 votes, which greatly increases the significance and reliability of these reviews. Taking into account the fact that, on average, a product has 277 reviews, the number of users voting in the form of "likes" and "dislikes" significantly exceeds the number of writing comments. The ability to track the popularity of a review is a very useful option for consumers.

Besides, individual characteristics of past reviews can influence the process of generating new reviews. In addition, the rating should be influenced by the perception of the quality of the product, i.e. the type of product.

Hypothesis 4: The probability of each rating depends on the type of product and individual motives of the user.

All suggested hypotheses were based on descriptive analysis of data and literature review in the first part of the article. In the next section we will present the empirical model designed to test these hypotheses.

4. The Empirical Model

To estimate the dynamics of online reviews, a variable “difference” was created to reflect the module of standard deviation of the user's assessment from the accumulated average rating for previous users. As the main goal of this research is to estimate factors influencing dynamic of online reviews, we need a measure showing how each following review tends to differ from overall average rate. If we find that deviation is growing, then user tends to differ and the question is what factors make them diverge from previous users. We would like to start with estimation of hypothesis that were not tested in previous papers. Then we will procced with estimation of personal motives and product types on reviews dynamic. As one of hypothesis states, one of the reasons can be in stronger influence of last reviews. The impact of the new responses is reflected in the variable STD_new10, which is equal to the standard deviation of the ratings of 10 reviews preceding this one. 10 was selected as threshold since this is the number of reviews reflected on one page in the Yandex.Market. Variable STD_old10 contains standard deviation of older reviews which were not included in the STD_new10 count. To account for the influence of the last 20 reviews, the variables STD_new20 and STD_old20 were introduced in the same way.

Table 6 shows that previous reviews influence the process of new reviews writing: there is positive influence of deviation from the average among previous users on each subsequent review. Besides, there is a difference in influence of new and old reviews: the newer reviews have a greater impact on the dynamics of the current review writing than the older ones. Even if this result seems intuitively obvious, it is nevertheless very important.

Since users rely more on the latest reviews, this fact may be used by companies to create a positive signal about the quality of the product by monitoring only the latest reviews.

It is interesting to note that total number of written reviews affects the number reviews which influence the current review. For example, for products with more than 200 reviews (a rounded median value), the threshold for the significance of the number of recent reviews increases: the user is guided by the last 20, not 10 reviews, which indicates that such products are characterized by a broader analysis of previous comments and the user psychologically feels the pressure of the amount of information available.

The table below shows results of both OLS (Ordinary Least Squares model) and FE for product category (fixed effects) models. The main difference of FE model is that it takes into consideration panel structure of the data, this model helps to address unobserved heterogeneity related to each product category characteristics constant over time. Thus, we add binary variable for each product category to control for differences in categories.

Table 6. The Difference in Influence Between New and Old Reviews

	n_reviews<200		n_reviews>200	
	OLS	FE	OLS	FE
STD_new10	0,217**	0,131**		
	-0,008	-0,006		
STD_old10	0,182**	0,063**		
	-0,012	-0,007		
average_grade	-0,310**	-0,552**	-0,371**	-0,634**
	-0,009	-0,013	-0,009	-0,011
lnaverage_price	-0,011**		-0,020**	
	-0,003		-0,002	
STD_new20			0,193**	0,137**
			-0,011	-0,005
STD_old20			0,104**	0,043**
			-0,015	-0,005
Constant	2,214**	3,333**	2,634**	3,704**
	-0,047	-0,061	-0,066	-0,053
N	3674	3674	3613	3613
p	0,000**	0,000**	0,000**	0,000**
r2	0,737	0,536	0,873	0,723
bic	-2721,8	-4842,76	-6399,96	-7761,82

Significance level: * — $p < 0,1$; ** — $p < 0,05$; *** — $p < 0,01$.

Yandex.Market not only offers the possibility to investigate quality of products and to read existing reviews, but also works as a service for comparing prices between stores, so that for each product you can see the minimum, maximum and average price. We expect that price category of the product can also be a factor influencing the dynamics. One of the reasons is laying in motives explanation. For example, for altruistic people we can expect more engagement in reviews activity for more expensive products as risk is growing with increase of price. For more expensive products we can also expect a larger gap between expected and received quality is needed to push the user to share experience. However, an important question is which price to use as determinant, as user can observe minimum and average price across stores.

Table 7 shows that the coefficient of average price logarithm is higher than the coefficient of minimum price logarithm, which means that average price has a more significant effect on the size of current user's deviation.

Table 7. Comparison of Minimum and Average Prices

	Model1	**Model2**
STD_new	0,217***	0,217***
	-0,008	-0,008
STD_old	0,182***	0,183***
	-0,012	-0,012
average_grade	-0,310***	-0,312***
	-0,009	-0,009
lnaverage_price	-0,011***	
	-0,003	
lnmin_price		-0,007**
		-0,003
Constant	2,214***	2,181***
	-0,047	-0,046
N	3674	3674
p	0,000***	0,000***
r2	0,737	0,736
bic	-2721,8	-2714,33

Significance level: * — $p < 0{,}1$; ** — $p < 0{,}05$; *** — $p < 0{,}01$.

In the final model of factors affecting online reviews dynamic were also used fixed effects for product categories. In Table 8 we present the results of factors of ratings dynamic for situations when there are less than 100 reviews.

Table 8. OLS Regression for Dynamic of Online Reviews

Variable	**Coefficient**	**SE**
STD_new	0,201***	-0,008
STD_old	0,166***	-0,012
average_grade	-0,319***	-0,009
lnaverage_price	0,10*	-0,06
category==GPS_navigator	0,113***	-0,03
category==TV_set	0,023	-0,025
category==air_conditioner	0,118***	-0,014
category==blender	0,091***	-0,015
category==camera	0,023	-0,015
category==electr_book	0,118***	-0,012
category==flatiron	0,082***	-0,015
category==haircutting	0,109***	-0,022
category==hairdrier	0,086***	-0,016
category==kettle	0,063***	-0,015
category==laptop	0,035***	-0,013
category==memory_card	0,023	-0,027

category==playstation	0,063***	-0,014
category==printer	0,138***	-0,012
category==refrigerator	-0,067**	-0,032
category==screen	-0,078***	-0,014
category==vacuum_cleaner	0,125***	-0,012
category==video_camera	-0,010	-0,028
Constant	2,035***	-0,07
N	3674	
p	0,000***	
r2_a	0,765	
bic	-2989,852	

Significance level: * — p <0,1; ** — p <0,05; *** — p < 0,01.

This model shows that standard deviation of current review's rating from the average is positively affected by the variance of previous reviews: an increase in the standard deviation of the last 10 responses by 1 increases the module of deviation by 0,2, for older reviews — by 0,16. In addition, as the average rating increases, this deviation decreases. Also, with increase in the product price by 1%, the deviation increases by 0,001 points. For products with low prices this factor can be not very significant, but for products in the high price category it can play an important role. In addition, there are significant differences in dynamics of online reviews between product categories.

One explanation can come from the theory of effectiveness of information transfer and the division into search products and products of experience. In addition, if we enter a variable of sequence in our model it turns to be statistically insignificant what can also be explained by the different direction of the effect of this change for the products of experience and products of search. To test this hypothesis, we used the methodology proposed in [Hong, Chen, Hitt, 2014]. All products differ in subjective and objective perception of the quality by consumers; therefore the main indicator of the type of products is the convergence of estimates in time or its absence. If products do not differ too much by main characteristics, then we can talk about one type of product for one category level. In order to divide products into search and experience products, we use a simple regression and look at the coefficient for sequence.

$$STD_{nij} = \beta_0 + \beta_1\, sequence_{nij} + \beta_2 I_j \quad (1)$$

for category level;

$$STD_{ni} = \beta_0 + \beta_1\, sequence_{ni} \quad (2)$$

for product level.

Where

STD_{nij} reflects cumulative standard deviation for nth review of product *i* in category *j;*

$sequence_{nij}$ is order I reviews history for nth review of product *i* in category *j;*

I_j stays for category *j*.

For search products there should be convergence of estimates and perception of the quality. In the case of experience products there will be observed an increase in variance or the absence of any trend due to the subjectivity of quality perception (see Table 9).

Table 9. Product Type Research

	OLS regression	FE regression	
Category	**Coefficient**	**Coefficient**	**Classification**
GPS devices	,0075303*** (,0017885)	,0088878*** (,00126)	Experience product
TVs	,0074633*** (,001573)	,0044616*** (,0016804)	Experience product
Air conditioners	,0093726*** (,0014869)	,0096551*** (,0011025)	Experience product
Blenders	,0075374*** (,0003625)	,0069316*** (,000358)	Experience product
Cameras	-,0007697*** (,000114)	-,0008705*** (,000084)	Search product
E-books	,0004272*** (,0002787)	,0016315*** (,0000873)	Experience product
Iron	,0053102*** (,0005395)	,0046685*** (,0004358)	Experience product
Hair clippers	-,0083088*** (,0021145)	-,0038414*** (,0014136)	Search product
Hair dryers	-,0035524*** (,0011499)	,001107 (,0007416)	Search product
Electric kettles	-,0011884*** (,0001415)	,0001985** (,0000849)	
Memory cards	,0048717* (,002001)	,0056614*** (,001538)	Experience product
Video game consoles	-,0009675*** (,000244)	-,0023711*** (,000104)	Search product
Printers	,0041294*** (,0005495)	,0039732*** (,0004002)	Experience product
Refrigerators	,0018406 (,0016169)	,0043503** (,0015055)	Experience product
Mobile phone	,0005597*** (,0000152)	,0005972*** (,0000108)	Experience product
Vacuum cleaners	,0012967*** (,000139)	,0008939*** (,000071)	Experience product
Washing machines	,0044766* (,0017218)	,0027921*** (,000655)	Experience product

Significance level: * — $p < 0{,}05$; ** — $p < 0{,}01$; *** — $p < 0{,}001$.

Based on the results of previous table, the binary variable “product_type” was encoded, receiving value 1 in case of experience product and used in the following research to identify differences between reviews.

Since experience products a perceived more subjectively, it should be reflected in the number of individual review characteristics. For the experience products one can expect more detailed, long reviews with a greater degree of involvement of the social response in the form of "likes" and "dislikes." A variable “vote” was created, reflecting the sum of "likes" and "dislikes" and popularity of reviews. To test the hypothesis that reviews for experience products should have a higher number of disagreements, we calculated the ratio of "dislikes" to "likes".

Table 10. Influence of Product Types on Main Individual Characteristics

	ln_comment	ln_advan	ln_disadvan	Vote
product_type	0,156***	-0,136***	0,258***	-0,305***
	(0,029)	(0,029)	(0,035)	(0,036)
Constant	5,415***	4,682***	4,340***	2,815***
	(0,025)	(0,024)	(0,030)	(0,031)
N	7015	7439	7212	7057
p	0,000***	0,000***	0,000***	0,000***

Significance level: *— $p < 0,1$; ** — $p < 0,05$; *** — $p < 0,01$.

This table shows that type of product has a significant impact on the key characteristics of a rating. For experience products, one can expect 17% longer comments. This suggests that the comments for products of experience are deeper and more detailed, since the description of their quality is more complicated than for search products. Similarly, the description of shortcomings of products is 30% more lengthy. This fact can also be explained by the difficulty in communication of dissatisfaction with the quality of experience products. It is worth noting that there is a completely different trend in “Advantage” section — this section is shorter for products of experience. The importance of the variable "vote" means that 35% less frequently are voted for reviews of product experiences than for search products. The variable that reflects the ratio of "likes" and "dislikes" does not show a significant dependence on the type of product.

To conclude, type of product affects not only the dynamics of ratings in reviews, but also their “Comment” section. There is also a significant difference in the popularity of such reviews. It can be assumed that the type of product determines not only the dynamics of the estimates, but also the length of the comment and involvement around these reviews.

5. Model of Probabilistic Distribution of Estimates

Previous models described how reviews deviate from each other and what factors influence this trend over time. However, these models cannot predict the direction of this deviation, i.e. when a user is going to submit low and high ratings. In addition, the influence of individual characteristics of previous reviews was not considered. In order to take into account the direction of the influence of individual characteristics of previous reviews on the probability to put certain rating, as well as for the possibility to identify individual user motives, we applied the model of ordered logit. The rating put by the user is a score from 1 to 5, with each point having a verbal interpretation. However, the difference in the user's perception of these scores varies considerably, for example, the difference between the rating of 5 and 4 points will be less critical for the user in choosing a product than the difference between 4 and 3. In addition, as noted in the first chapter of this paper, there are papers in literature emphasizing difference in positive and negative reviews. To check the direction of influence, three models were built. Prefix l_ before variables reflects that we take into consideration parameter of last review before current one. The results of the evaluation are given in Table 11.

Table 11. Ordered Logit Models for Review's Rating Estimation

	Model1	**Model2**	**Model3**
average_grade	1,121***	0,086***	0,087***
l_grade	0,125***	0,480***	1,071***
product_type	-0,356***	-0,333***	-0,377***
l_grade_days	-0,003***		
l_grade*l_sequence	-0,003**	-0,001***	-0,001*
l_grade*l_ln_likes	-0,000		
l_grade*l_ln_dislikes	0,014**	0,001**	0,001***
STD		-1,449*	
STD_new			-0,183**
STD_old			-0,086
lnaverage_price			1,077*
cut1	2,277 **	-1,993**	2,536**
cut2	2,977 **	-1,300*	3,230**
cut3	3,608 **	-0,681	3,824**
cut4	4,593 **	0,296	4,763**
N	5981	7517	6501
chi2	773,810**	1003,092**	822,296**
bic	14148,2	17898	15830,13

Significance level: * — $p < 0,1$; ** — $p < 0,05$; *** — $p < 0,01$.

Where *average_grade* stays for the average rating for the product before current review;

l_grade – rating of the previous user;

product_type – binary variable that takes the value 1 for experience products;

l_grade_days – number of days passed between writing of current and previous reviews;

STD – standard deviation of all previous reviews;

STD_new – standard deviation of last 10 reviews;

STD_old – standard deviation of all reviews written earlier than last 10 reviews;

lnaverage_price – logarithm of average price of product.

Next variables are cross-products and show how influence of previous grade can change if control for its sequence in reviews' chain, its popularity and the level

*l_grade*l_sequence* – change of influence of last grade based on its sequence number;

*l_grade*l_ln_likes* - change of influence of last grade based on how many users supported it by likes;

*l_grade*l_ln_dislikes* - change of influence of last grade based on how many users disagreed with previous users in form of dislikes;

Due to the specific nature of the ordered logit model, these coefficients cannot be directly interpreted, while conclusions can be made about the direction of influence.

Model 1 is called to identify effect of individual characteristics of the previous user's review on current rating, to check existence of the self-enhancement motive for users in the Russian market. The influence of the previous user's experience, his reviews history, the content of the user's comment, the number of positive and negative votes for the review, the number of days between reviews were investigated. The model helped to reveal a number of interesting patterns that are in contradiction with the conclusions of some papers reviewed previously. This comparison is presented in Table. 12.

Table 12. Investigation of Individual Motives

Criterion	This paper	Previous papers
Relationship between current rating and average overall rating of previous reviews	Positive relationship: the higher the current average grade, the higher the probability that the next user will put a higher rating; users are guided by the desire to share good impressions	Negative relationship between the prevailing opinion about the product among previous users and the current user [Li, Hitt, 2008]
Relationship between last rating and current rating	A user tends to put a higher rating than the previous user	Users tend to distinguish themselves from the crowd by putting very negative rating [Hu, Liu, Zhang, 2008]
Relationship between the frequency of reviews and the likelihood of a maximum rating	There is a negative correlation between the number of days between two reviews and the probability to give a higher rating	The more days pass after the last review, the more likely the next review will contradict to the last [Duan, Gu, Whinston, 2005]
Relationship between number of reviews and new rating	With the increase in number of reviews, users are more likely to submit a lower rating than the previous user	With a sufficiently large number of reviews, users tend to write only in case of negative experience [Hu, Liu, Zhang, 2008]
Relationship between expert's rating and current rating	Previous user's experience in usage of product (as well as in number of reviews written) is not a statistically significant factor affecting the probability to put exact rating	Ratings of more experienced users have a greater impact on the ratings given by the user than general reviews [Gu, Lin, 2006]
Relationship between length review and the next evaluation	Possible dependence between the comment length of the previous user, which reflects how informative review was and rating of the following user was checked. Statistically significant dependence wasn't found	The longer is the comment, the more likely that rating is negative [Hu, Liu, Zhang, 2008]

It is also worth noting that the influence of "dislikes" was found statistically significant. The next review tends to be better than the previous one if the latter has many dislikes. This fact indicates that the user may explain unpopularity of the previous comment by its low evaluation and try to improve the rating of the product by a more positive review (this is typical for users of the US and Chinese markets).

The product type was found statistically significant. It means that products with a higher degree of subjectivity in quality perception usually have lower grades.

Models 2 and 3 reflect the difference in the variation effect. New reviews have a more significant impact on users' decisions than the variance of old reviews of this product, and it is better to consider only last reviews' variation than aggregate variation of all reviews as it is usually used in papers.

Model 3 is our final model with application of price effects. When the price of product increases, we expect an increase in the likelihood to put a positive rating. Since for most categories, prices within a category do not differ significantly, it can be said that this positive effect is related to the psychological characteristics of users. When buying expensive products, users are less likely to admit if the product has poor quality [Tatzel, 2003]. Another explanation is that users are more attentive to the choice of more expensive products.

Marginal effects reflect the change of probability of falling into a certain category as the variable increases by one. Results for Model 3 are shown in the table 13.

Table 13. Marginal Effects

Variable	**5**	**4**	**3**	**2**	**1**
l_grade	0,021600	-0,005461	-0,004885	-0,004668	-0,006586
average_grade	0,265589	-0,067144	-0,060067	-0,057395	-0,080982
product_type	-0,093656	0,023678	0,021182	0,020240	0,028557
l_gradel_l_dislikes	0,000230	-0,000058	-0,000052	-0,000050	-0,000070
STD_new	-0,045521	0,011508	0,010295	0,009837	0,013880
l_gradel_sequence	-0,000021	0,000005	0,000005	0,000004	0,000006
ln_average_price	0,018411	-0,004655	-0,004164	-0,003979	-0,005614

Thus, when the average rating increases by 1 unit, the probability of setting the next rating as excellent increases by 26,5%. Among other significant factors which increase the likelihood of a positive evaluation one can distinguish the logarithm of the price of products and evaluation of the last user.

One of the factors negatively influencing probability of positive rating is the experience product type. The difficulty of assessing quality before buying it by 9% reduces the likelihood to put maximum rating in review. This conclusion is important for sellers of experience products. As was noted in the literature overview, there is positive relationship between average rating and sales volume as well as between the share of positive reviews and the popularity of the product. Consequently, sellers may be interested in reducing the effect of the product type on the likelihood of getting low rating reviews. Since the type of product is associated with the lack of user's opinion convergence, this indicates that online reviews are not an effective tool for obtaining information about these products. In order to increase the level of awareness of users about such products, it is necessary to communicate information about product in another way: free demonstrations of product functionality and operation, opportunity to try the product in the store. It is also possible along with reviews to make video reviews of products and place them on the same sites as extra information about products. Even if such reviews can be found in the Internet, they are not always made by experienced people. Product surveys posted on special sites, where there are both user reviews and product descriptions, should have a greater impact.

In addition, the positive attitude of users identified for the Russian market and absence of self-enhancement motive that is postulated for other countries can also be taken into account by sellers for marketing strategy development.

6. Conclusion

This work is devoted to online reviews dynamics in the Russian market of electronics. Although other researchers focused on the impact of aggregated online ratings on sales, we decided to identify factors that influence decisions to write an online review. We built an empirical model assesses the factors that affect the size of the current user's deviation from the average rating. We show that there is a difference in influence between old and new ratings on the subsequent ones. In particular, an increase of standard deviation between users of the last ten reviews causes an increase of deviation for the current review. Products with a long history of reviews are characterized by deeper reviews search of current user and the number of more significant reviews increases. This can be taken into account by a company which receives negative feedbacks on the site and tries to correctly determine the number of positive feedback to create a positive image.

This research also shows significant difference in the influence of average and minimum prices: average price better explains dynamics of the rating. Significant differences in cumulative standard deviation also come from product type identification.

Product type influence was examined for durable electronic products. Categories of search products were characterized by convergence of reviews ratings. For such products, online reviews system forms correct perception of product quality. In case of experience products sellers need to look for other ways of product promotion, where buyers can directly try and examine product before buying it. Here the product type only influences rating dynamics, but also impacts users' activity in voting and showing their level of agreement as well as comment section size and review's depth.

The last part of the study investigates influence of individual characteristics of previous reviews as well as motives for review's creation. Empirical analysis shows that even if a lot of papers postulate significance of individual characteristics, most of them cannot predict rating of the next user. It has been found that for Russian users it is not typical to write a review with opposite assessment in relation to the previous commentator. On the contrary, there is a statistically significant tendency to write more positive reviews than the average for previous users. There is also a positive relationship between the previous user's rating and the probability that the next user will give a higher grade.

One of the possible directions for further research is to investigate foreign online markets such as Ebay.com and Aliexpress.com which become more and more popular among Russian consumers. For such platforms, online reviews are almost the only way to learn about a product or sellers.

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